Development Of An On-line Adaptive ANN-based Controller For A Direct Expansion Air Conditioning System

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ABSTRACT

An on-line adaptive artificial neural network (ANN)-based controller has been developed for an experimental DX A/C system. It controls the indoor air temperature and humidity simultaneously by varying the compressor speed and supply fan speed in a space served by the experimental DX A/C system. The ANN-based direct inverse control (DIC) strategy was adopted in the development of the controller and the specialized training method was used to on-line update an ANN-based model and an inverse model used in the controller. The controllability tests including the command following test and the disturbance rejection test were carried out using the experimental DX A/C system, and the test results showed that the on-line adaptive ANN-based controller developed was able to control indoor air dry-bulb temperature and wet-bulb temperature outside the operating conditions within which the models were trained, with a high control accuracy.

1. INTRODUCTION

Direct expansion (DX) air conditioning (A/C) has been widely used in small- to medium-scaled buildings and possesses many advantages over conventional chilled-water based A/C systems. These advantages include higher energy efficiency and lower cost to own and maintain the systems. A DX A/C system can offer different levels of space air temperature for the control of indoor thermal comfort. However, it is difficult to satisfy both the indoor temperature control and humidity control simultaneously using a DX A/C system with a single speed compressor and a single speed supply fan, which may deter the wider use of DX A/C systems (Qi and Deng, 2009).

The traditional method for indoor humidity control for central A/C systems is reheating. This method is costly and energy inefficient since it uses a great deal of energy to overcool the air, and then more energy to reheat the air to a suitable supply temperature. The use of reheating is however uncommon for DX A/C systems, nonetheless controlling indoor humidity at an appropriate level while also maintaining suitable indoor air temperature using a DX A/C system is difficult, since the cooling coil in a DX A/C system must perform both air cooling and dehumidification simultaneously. Most DX A/C systems are currently however equipped with a single-speed compressor and supply fan, relying on on-off cycling compressor as a low-cost approach to maintain only indoor air dry-bulb temperature. This results in either space overcooling or an uncontrolled equilibrium indoor relative humidity (RH) level.

With the advancement of low-cost variable speed drive (VSD) technology, it offers tremendous opportunities for improving indoor thermal control and energy efficiency for DX A/C systems. Compressor speed can be continuously varied to modulate the output cooling capacity to match the space actual thermal load. The supply fan speed can be also altered to affect both sensible heat and latent heat transfer rates across a heat exchanger. Therefore it is possible to simultaneously control indoor air temperature and humidity by varying speeds of both compressor and supply fan in a DX A/C system.

On the other hand, artificial neural network (ANN) has been proven to be a useful tool in modeling the dynamic operating performance of a nonlinear multivariable system. This is because it has been shown that ANN has a powerful ability in recognizing accurately the inherent relationship between any set of inputs and outputs without requiring a physical model. This ability is essentially independent of the system complexity such as nonlinearity, multiple variables, coupling, with noise and uncertainty (Diaz *et al*., 1999, Haykin, 1999). An ANN-based control strategy which could deal with a nonlinear MIMO complex system based on an ANN-based model can then be developed. As an intelligent nonlinear dynamic control method, an ANN-based control strategy offers a viable solution to the control over complex systems (Norgaard *et al*., 2000, Yang, 2008). No previously related research work on controlling indoor air temperature and humidity simultaneously through an on-line adaptive control strategy developed using ANN can be indentified in open literatures. Therefore it is necessary to fill the gap and embark on a study on developing an on-line adaptive ANN-based control strategy that can simultaneously control indoor air temperature and humidity by varying the speeds of both compressor and supply fan in a DX A/C system.

The organization of the paper is as follows. Section 2 describes briefly an experimental DX A/C system and its dynamic model. The design of the MIMO controller based on the dynamic model is presented in Section 3. The results of controllability tests of the MIMO controller are reported in Section 4.

2. DESCRIPTION OF THE EXPERIMENTAL DX A/C SYSTEM

The experimental DX A/C system was mainly composed of two parts, i.e., a DX refrigeration plant (refrigerant side) and an air-distribution sub-system (air side). Its simplified schematic diagram is shown in Figure 1. The major components in the DX refrigeration plant included a variable-speed rotary compressor, an electronic expansion valve (EEV), a high-efficiency tube-louver-finned DX evaporator and an air-cooled tube-plate-finned condenser. The evaporator was placed inside the supply air duct on the air side to work as a DX air cooling coil. The nominal output cooling capacity from the DX refrigeration plant was 9.9 kW. The working fluid of the plant was refrigerant R22, with a total charge of 5.3 kg. The air side included an air-distribution ductwork, a variable-speed centrifugal supply fan, and a conditioned space. Inside the space, there were sensible heat and moisture load generating units (LGUs), simulating the cooling load in the space.

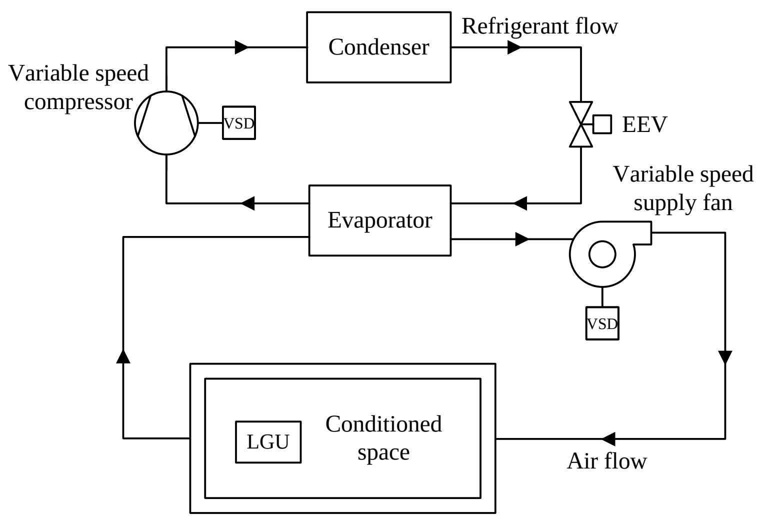


Figure 1: The schematic diagram of the experimental DX A/C system

3. ON-LINE ADAPTIVE ANN-BASED CONTROLLER DESIGN

The condenser cooling airflow rate was maintained constant at 3100 m^3/h, with its inlet temperature fixed at 35 ℃. The degree of refrigerant superheat was maintained constant at 6 ℃ by using the EEV, which was controlled by a built-in conventional PID controller in the DX A/C system. The objective of the on-line adaptive ANN-based controller was to control the indoor air temperature and humidity simultaneously by varying the compressor speed and supply fan speed in a space served by the experimental DX A/C system.

An ANN-based steady-state model, an ANN-based dynamic model and an ANN-based controller for the experimental DX A/C system have been developed and were previously reported (Li *et al*., 2011a, Li *et al*., 2011b). The on-line adaptive ANN-based controller was designed by applying the concept of adaptive control to the ANN-based controller developed to make the controller workable at a wider operation range of the DX A/C system. The on-line adaptive ANN-based controller composed of an ANN-based dynamic model and an ANN-based inverse model, both of which were initially off-line trained using the general training method and on-line updated during the process of training using the specialized training method.

The specialized training algorithm is shown as follows: the specialized training aims at minimizing the more goal directed criterion of the following type:

$$E = \frac{1}{2}\sum_i (y_i - r_i)^2 \tag{1}$$

The back propagation (BP) algorithm implements a gradient descent in E and upgrades the weights of the ANN-based inverse model, i.e., W, in the way:

$$W(t+1) = W(t) - \eta \frac{\partial E}{\partial W(t)} \tag{2}$$

To process $\frac{\partial E}{\partial \boldsymbol{W}}$, the chain rule was used:

$$\frac{\partial E}{\partial \boldsymbol{W}} = \frac{\partial E}{\partial \boldsymbol{y}} \frac{\partial \boldsymbol{y}}{\partial \boldsymbol{u}} \frac{\partial \boldsymbol{u}}{\partial \boldsymbol{W}} \tag{3}$$

The value of $\frac{\partial E}{\partial \boldsymbol{y}}$ could be calculated as follows:

$$\frac{\partial E}{\partial \boldsymbol{y}} = \sum_i (y_i - r_i) \tag{4}$$

The ANN-based dynamic model of the system is identified to provide estimates of the Jacobians of the system:

$$\frac{\partial y(t+1)}{\partial u(t)} \approx \frac{\partial y_m(t+1)}{\partial u(t)} \tag{5}$$

Where $y_m(t+1)$ refers to the outputs from the ANN-based dynamic model at time step (t+1) with the same inputs as the system. It is the predicted results of the ANN-based dynamic model.

The operating principle of the ANN-based on-line adaptive controller is illustrated in Figure 2. During the process of control, the on-line adaptive ANN-based controller was on-line updated by first updating the ANN-based dynamic model using the specialized training method and then updating the ANN-based inverse model using the specialized training method according to the changes in control references and real-time operating parameters of the DX A/C system. Since the ANN-based dynamic model was updated on-line before updating the ANN-based inverse model, the updating of the ANN-based inverse model could use the Jacobian of the system which was evaluated by the last updated ANN-based dynamic model. In this way, the on-line adaptive ANN-based controller could adapt to the changes in actual operating conditions for the DX A/C system. The updating of the ANN-based dynamic model and ANN-based inverse model was carried out continuously every 60 s in the current study.

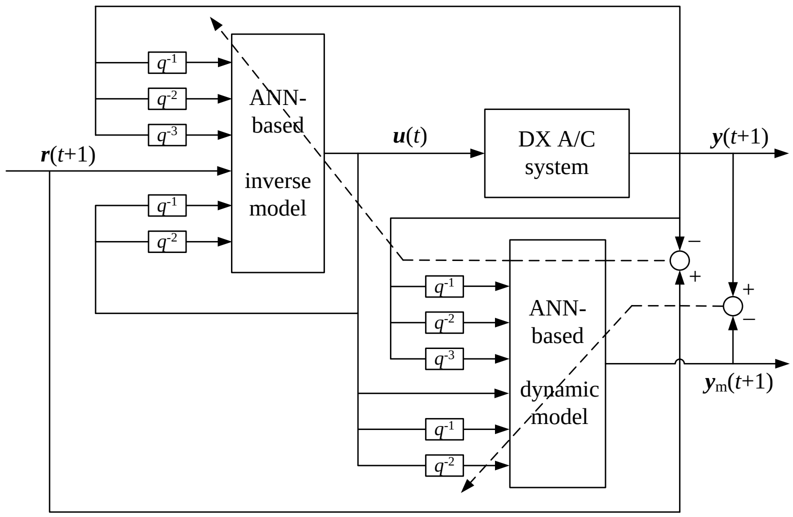


Figure 2: The schematics of the on-line adaptive ANN-based controllers

In the current study, both the ANN-based dynamic model and ANN-based inverse model were initially off-line trained around the indoor air dry-bulb temperature and wet-bulb temperature setpoints of 24 ^oC and 17.1 ^oC respectively (or 50% RH). The controllable ranges of the ANN-based on-line adaptive controller were designed to be extended to 20 ^oC to 28 ^oC for indoor air dry-bulb temperature and 13 ^oC to 21 ^oC for indoor air wet-bulb temperature, which were commonly required for indoor thermal comfort.

4. CONTROLLABILITY TESTS

After developing the on-line adaptive ANN-based controller for the experimental DX A/C system as reported above, the controllability tests to examine its control performance were carried out using the experimental DX A/C system. When carrying out the tests, the controller was digitally implemented in the form of a computer program, with suitable interfaces for collecting data and outputting control actions such as varying speeds of compressor and supply fan via variable speed drives. The following two types of controllability tests were carried out:

(1) Command following test: when the setpoints of indoor air dry-bulb temperature and wet-bulb temperature were changed, the controller was expected to respond so that indoor air temperature and moisture content could be maintained at their respective new setpoints.

(2) Disturbance rejection test: the output variables of the DX A/C system, i.e., indoor air dry-bulb temperature and wet-bulb temperature were to be maintained at their respective setpoints when space sensible and latent cooling loads were subjected to disturbances.

4.1 Command Following Test (Exp I-1 and I-2)

Figures 3 to 4 show the results of command following tests for the on-line adaptive ANN-based controller. The initial settings of indoor air conditions were T_{db} = 27 ℃ and T_{wb} = 20 ℃ in Exp I-1, and T_{db} = 21 ℃ and T_{wb} = 14 ℃ in Exp I-2. At 300 s into the test, the above settings were altered to T_{db} = 25 ℃ and T_{wb} = 18 ℃ in Exp I-1, and T_{db} = 23 ℃ and T_{wb} = 16 ℃ in Exp I-2, and the controller was immediately responded by simultaneously varying the compressor and supply fan speeds. T_{db} and T_{wb} reached their respective new setpoints in about 1200 s and 2400 s, respectively, and were maintained steadily in the remaining time of the testing period. As seen in both tests, T_{db} was very stable and accurate during the steady periods, and the fluctuations of T_{wb} during the steady periods were all within 0.3 ℃. These suggested that the ANN-based on-line adaptive controller was able to track the changes in its indoor air dry-bulb temperature and wet-bulb temperature settings within their controllable ranges. Since both the ANN-based dynamic model and inverse model were on-line updated continuously, the speeds of compressor and supply fan would keep changing to deal with the disturbances even when the controlled parameters did not significantly fluctuate.

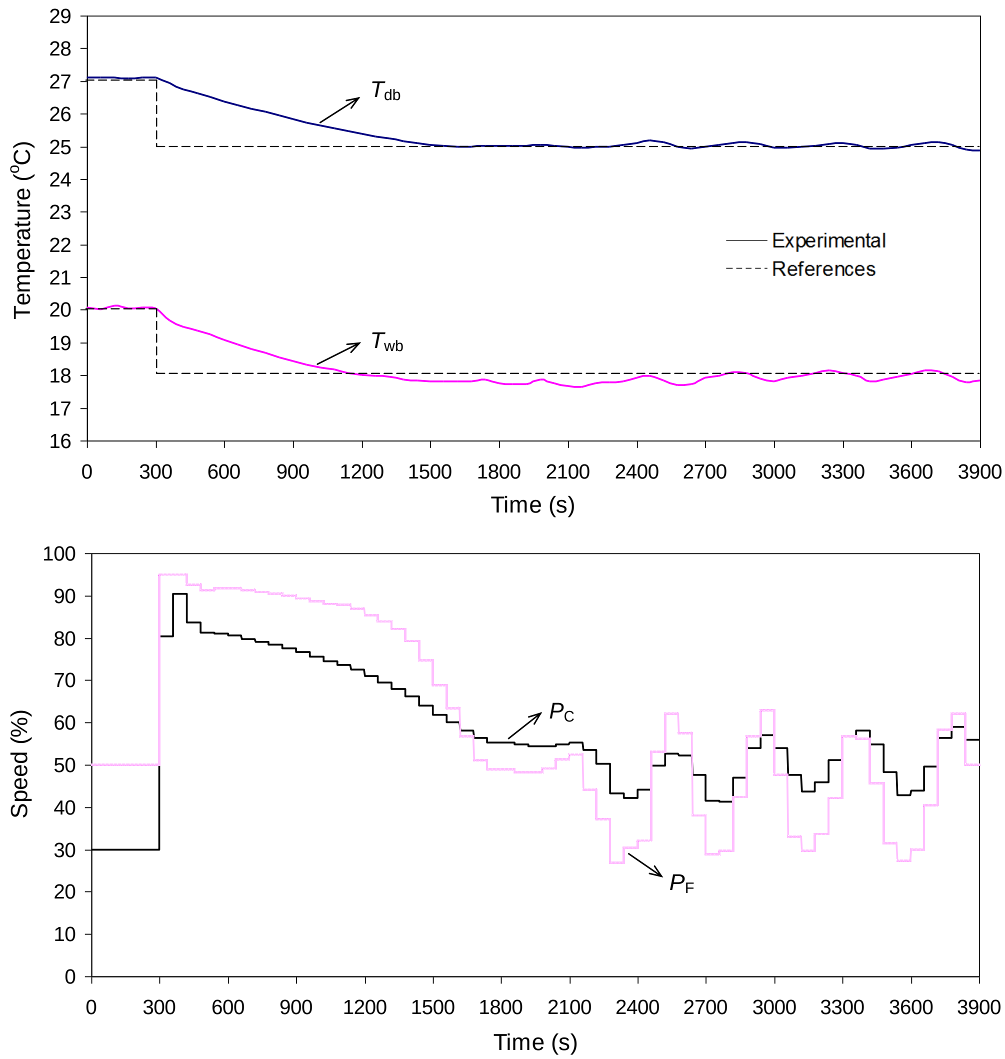
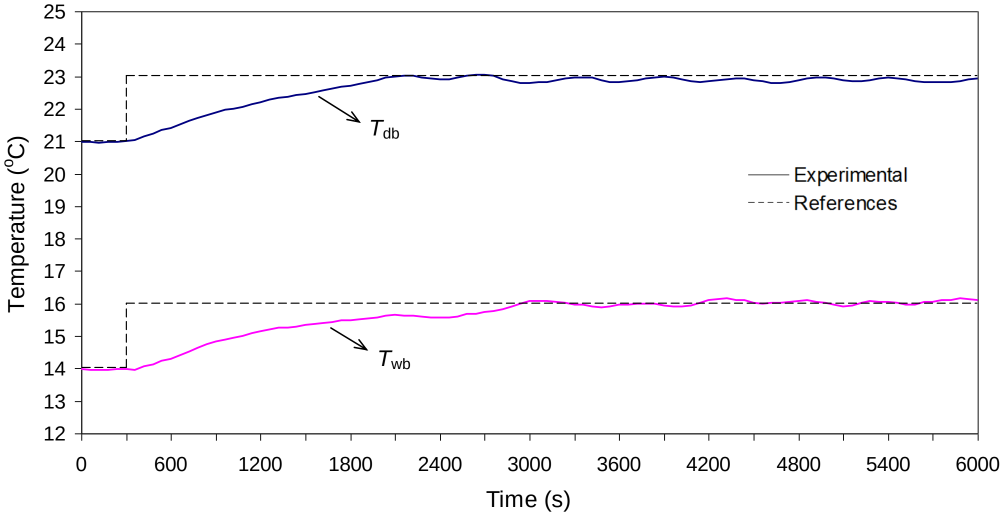


Figure 3: The variations of the indoor air dry-bulb and wet-bulb temperatures and compressor and supply fan speeds in Exp. I-1



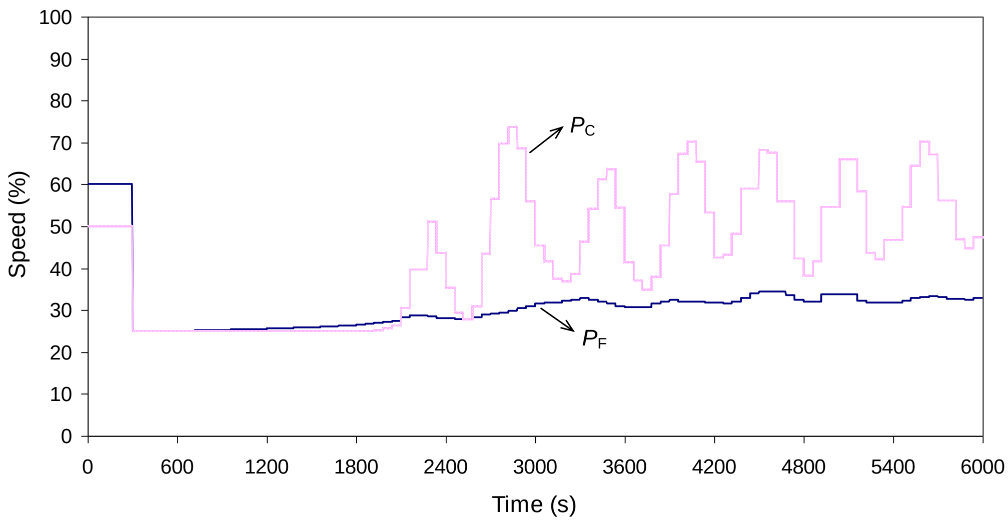


Figure 4: The variations of the indoor air dry-bulb and wet-bulb temperatures and compressor and supply fan speeds in Exp. I-2

4.2 Disturbance Rejection Test (Exp II-1)

In this test, the indoor air settings were T_{db} = 26 ℃ and T_{wb} = 19 ℃. The ANN-based controller was enabled when the deviation for either the measured indoor air dry-bulb temperature or the measured indoor air wet-bulb temperature was greater than ±0.5 ^{o}C. Figure 5 presents the results of disturbance rejection test for the on-line adaptive ANN-based controller. As seen, prior to the introduction of disturbance at 300 s into the test, indoor air temperatures were steadily maintained at their respective setpoints. At 300 s into the test, space sensible load was reduced from 4.5 kW to 3.4 kW and space latent load from 3.0 kW to 2.4 kW, respectively. In response to the disturbances, both T_{db} and T_{wb} were gradually decreased. At about 960 s into the test, when T_{db} dropped to 25.5 ℃, the controller was enabled. The variation profiles of compressor speed and supply fan speed are also shown in Figure 5. Indoor air dry-bulb and wet-bulb temperatures went back to their respective setpoints in about 800 s and were maintained steadily thereafter for the rest of the test period. The fluctuations of T_{db} and T_{wb} during the steady period were within 0.3 ℃. Therefore, the on-line adaptive ANN-based controller was able to maintain indoor air dry-bulb and wet-bulb temperatures at their respective set points after indoor thermal loads were varied, achieving a satisfactory control performance in the disturbance rejection test.

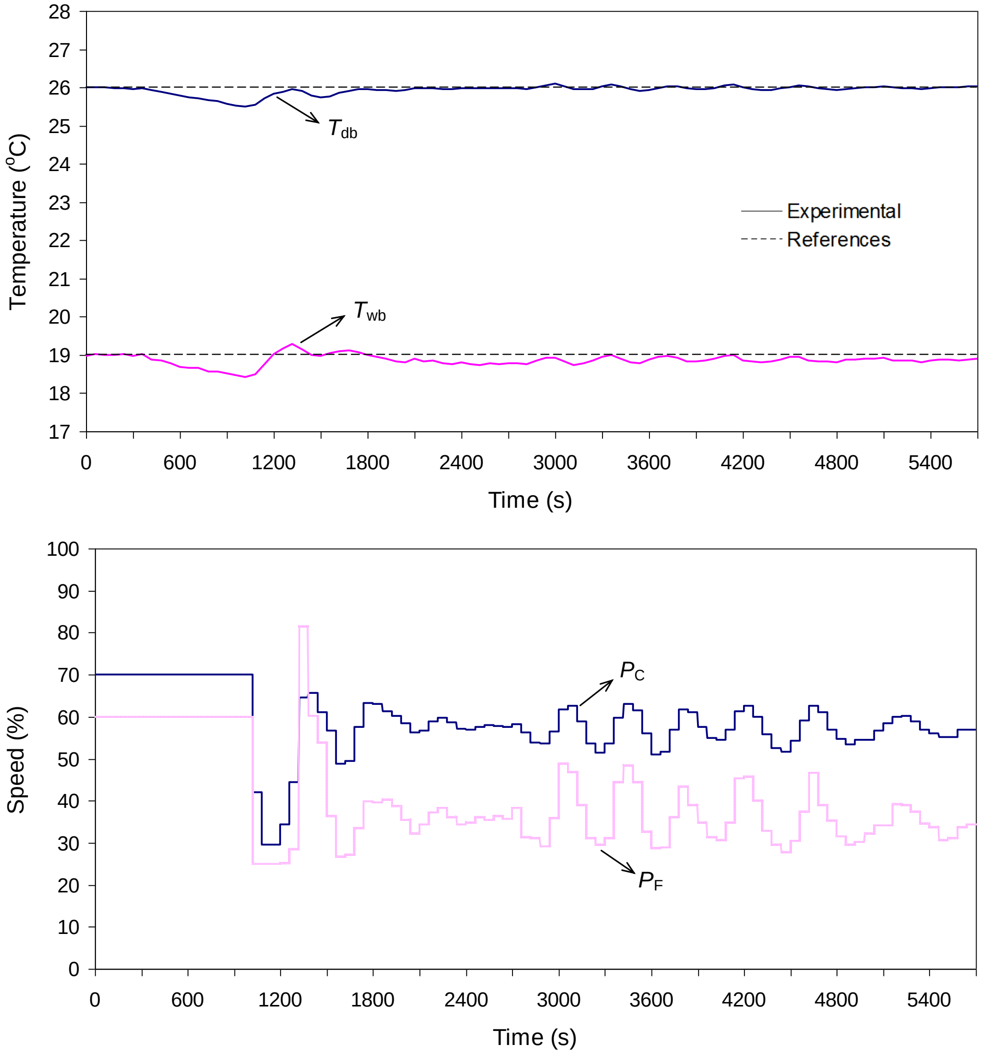


Figure 5: The variations of the indoor air dry-bulb and wet-bulb temperatures and compressor and supply fan speeds in Exp. II-1

5. CONCLUSIONS

An on-line adaptive ANN-based controller for simultaneously controlling temperature and humidity in a DX A/C system has been developed and reported in this paper. Controllability tests, including command following test and disturbance rejection test, show that the on-line adaptive ANN-based controller developed can effectively control the temperature and humidity in conditioned space by simultaneously varying compressor speed and supply fan speed outside the operating conditions within which the models were trained, with a high control accuracy in DX A/C system.

NOMENCLATURE

E	Error between the system outputs and the control references	-
P_C	Percentage of the maximum compressor speed	%
P_F	Percentage of the maximum supply fan speed	%
q	Time delay operator	-
r	Control reference	^{o}C

t	Time instant	-
T	Indoor air temperature	^oC
u	Inputs to a system	-
W	Synaptic weights	-
y	Outputs from a system	-
η	Learning rate	-

Subscripts

db	Dry-bulb temperature
i	Number of output variables
m	ANN-based dynamic model
wb	Wet-bulb temperature

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